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An advanced model for the efficient and reliable short-term operation of insular electricity networks with high renewable energy sources penetration

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ABSTRACT

This paper presents an overview of the different methodologies and mathematical optimization models developed in the framework of the EU-funded project SiNGULAR towards the optimal exploitation and efficient short-term operation of RES production in insular electricity networks. Specifically, the algorithms employed for the creation of system load and RES production scenarios that capture the spatial and temporal correlations of the corresponding variables as well as the procedure followed for the creation of units' availability scenarios using Monte Carlo simulation are discussed. In addition, the advanced unit commitment and economic dispatch models, that have been developed for the short-term scheduling of the conventional and RES generating units in different short-term time-scales (day-ahead, intra-day, and real-time) are presented. Indicative test results from the implementation of all models in the pilot system of the island of Crete, Greece, are illustrated and valuable conclusions are drawn.

Contents

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1. Introduction

The increased use of energy from Renewable Energy Sources (RES), together with Demand-Side Management (DSM), energy savings and increased energy efficiency, constitute important parts of the package of measures needed to reduce Greenhouse Gas (GHG) emissions that will help Europe comply with the Kyoto Protocol. The European target "20–20–20" implies [1]: (a) a reduction in European Union's (EU) greenhouse gas emissions of at least 20% below 1990 levels, (b) 20% reduction in primary energy use compared with projected levels, to be achieved by improving energy efficiency, and (c) 20% of EU energy consumption to come from renewable resources.

The latter goal motivated the EU countries to incentivize the increase of RES installed capacity, with particular emphasis on generating electricity from wind and more recently from solar resources. Large RES plants have already been constructed and operated across Europe, whereas the integration of new small and large RES projects continues aggressively. The share of RES in the electricity production is expected to increase to 30–35% by 2020 [2].

A large share of the recent RES installed capacity has already taken place in insular electricity grids, since these regions are preferable due to their high RES potential. However, the increasing share of RES in the generation mix of insular power systems presents a big challenge in the efficient management of the insular networks, mainly due to the limited predictability and the high variability of renewable generation, features that make RES plants non-dispatchable, in conjunction with the relevant small size of these networks.

In this context, the recently launched collaborative project SiNGULAR (Smart and Sustainable Insular Electricity Grids Under Large-Scale Renewable Integration), an EU-funded project under the 7th Framework Programme (FP7) aims at investigating the effects of large-scale integration of RES and DSM on the planning and operation of insular (non-interconnected) electricity grids, proposing efficient measures, solutions and tools towards the development of a sustainable and smart grid. Different network operation procedures and tools, based on innovative approaches of predictive electricity network operation, are being developed. A set of electricity network planning procedures and tools are also being developed to implement robust insular electricity network planning. The goal is the generation of effective solutions and information so that the integration of insular and highly variable energy resources is maximized. The operation and planning tools and procedures are being applied in different insular electricity grids across Europe (pilot sites), allowing the development of generalized guides of procedures and grid codes specific for future generation of smart insular electricity grids.

Among others, in the framework of SiNGULAR, various methodologies and software tools are being developed and implemented for the optimal short-term scheduling of insular electricity networks, taking into account the stochastic nature of various system and unit parameters, such as the system load, the RES production, the unit availability, etc.

In this paper, an overview of the different methodologies and mathematical optimization models developed towards the optimal exploitation and efficient short-term operation of RES production in insular electricity networks is presented. Specifically, the algorithms employed for the creation of system load and RES production scenarios that capture the spatial and temporal correlations of the corresponding variables as well as the procedure followed for the creation of units' availability scenarios using Monte Carlo simulation are discussed. In addition, the advanced unit commitment and economic dispatch models, that have been developed for the short-term scheduling of the conventional and RES generating units in different short-term time-scales (day-ahead, intra-day, and real-time) are presented.

The remainder of the paper is organized as follows: Section 2 describes the scenario generation and scenario reduction procedures for the description of the uncertain system parameters, namely RES generation, system load and units' availability. Section 3 describes the proposed advanced mathematical optimization models, namely unit commitment and economic dispatch models, for the short-term scheduling of the conventional and RES generating units in different short-term time-scales. In addition, indicative results from their coordinated implementation in the insular power system of Crete, Greece, are presented. Finally, in Section 4 valuable conclusions are drawn and indicative emerging methods and tools to address the challenges of the integration of large amounts of RES in insular electricity grids are highlighted.

2. Scenario generation methodologies

2.1. Scenario generation for RES injection

In order to create scenarios for RES injection, time series analysis methodologies are employed. Specifically, a process that combines a scenario generation technique of an original (extended) set of scenarios with a technique to reduce the number of scenarios is followed. An additional methodology for creating spatial cross-correlated scenarios is also applied.

The scenario generation technique of the initial (extended) set of scenarios using time series analysis techniques is based on a sampling approach. Specifically, the appropriate forecasting model for the random process under study (e.g. PV or wind power generation) is first determined. This forecasting model can be either a seasonal Autoregressive Integrated Moving Average (ARIMA) model or an Artificial Neural Network (ANN) model. In the following paragraphs the basic features of both forecasting models are presented and the adopted scenario generation procedure is described.

2.1.1. ARIMA models

A class of time series techniques, namely ARIMA, can be employed for the short-term forecasting of RES injection. ARIMA is a method first introduced by Box and Jenkins [3] and is one of the most popular methods for time series forecasting.

In general, for stationary time series a simple Autoregressive Moving Average model, ARMA (p, q), is used, whose analytical mathematical expression is as follows:

$$y_t = \sum_{j=1}^{p} \varphi_j y_{t-j} + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{1}$$

where $\varphi_1, \varphi_2 ..., \varphi_p$ are the p parameters of the autoregressive polynomial and $\theta_1, \theta_2 ..., \theta_q$ are the q parameters of the moving average polynomial. The term ε_t in the Eq. (1) stands for an uncorrelated normal stochastic process with zero mean and standard deviation σ. The stochastic process ε_t is also referred to

Table 1
RES generation forecasting models characteristics.

RES Type	Forecasting Model	Model inputs	Model output
PV	ARIMA	• PV production of previous hours, days, week (t-1, t-2,…, t-n) • Total daily solar radiation ✓ Previous days (historical data) ✓ Next day (Forecast data)	Hour-ahead PV production forecast
PV	Artificial Neural Network	• PV production of previous hours, days, week (t-1, t-2,…, t-n) • Total daily solar radiation ✓ Previous days (historical data) ✓ Next day (Forecast data) • Hour of the day • Day of the year	Hour-ahead PV production forecast
Wind	Artificial Neural Network	• Wind production of previous hours, days, week (t-1, t-2,…, t-n) • Hourly wind speed ✓ Previous days (historical data) ✓ Next day (forecast data) • Hour of the day • Day of the year	Hour-ahead wind production forecast

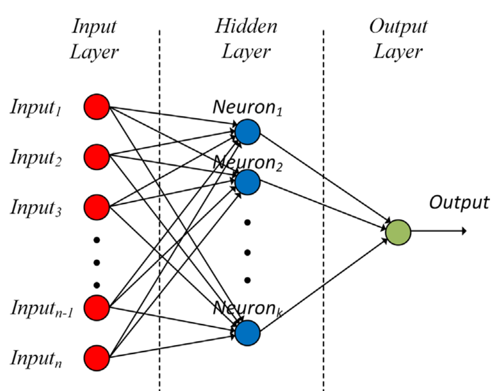

Fig. 1. Graphical illustration of an ANN model.

as white noise, innovation term, or error term. In case that the original time series, y_t, is non-stationary, a more complex model, namely Autoregressive Integrated Moving Average model, ARIMA(p, d, q), is constructed as follows. First, a stationary time series, z_t, is derived by suitable (d-th order) differentiation of the original non-stationary time series, y_t: $z_t = \nabla^d y_t = (1-B)^d y_t$, where $B(y_t) = y_{t-1}$. Then a suitable ARMA (p, q) model is derived for the new stationary time series, z_t, as in (1), where y_t is substituted with z_t.

A variation of the classical ARIMA model, namely the seasonal ARIMA model (i.e. SARIMA) is used here as the most appropriate time series model for the PV production forecasting. The seasonal ARIMA model is generally referred to as SARIMA $(p,d,q) \times (P,D,Q)_S$, where p, d, q and P, D, Q are non-negative integers that refer to the polynomial order of the autoregressive (AR), integrated (I), and moving average (MA) parts of the non-seasonal and seasonal components of the model, respectively and s defines the seasonal period.

The model development was based on the Box–Jenkins methodology, which consists of four iterative steps: (a) Identification, (b) Estimation, (c) Diagnostic Checking and (d) Forecasting. Further details on the description of the adopted methodology can be found in [3].

Finally, the developed SARIMA model was further improved by incorporating short-term solar radiation forecasts derived from Numerical Weather Prediction (NWP) models. In Table 1 the inputs and the output of the SARIMA model associated with the PV production forecast are presented.

2.1.2. Artificial neural networks

Artificial Neural Networks (ANN) are data processing systems that simulate the operation of the biological nervous system. They are widely used in numerous applications due to their ability to estimate both linear and non-linear dependencies between two or more variables.

ANN comprise a set of basic processing units known as artificial neurons, or simply neurons, in proportion to the terminology used for biological neurons. The neurons are arranged in layers and are connected by links, which are assigned appropriate weighting factors (see Fig. 1). The inputs of a neuron are the outputs of the neurons of the previous layer multiplied by their respective weighting factors of their links. The output of the neuron is then used as the input for the neuron of the next layer.

Each layer has also a polarization term (always equal to one), which is also connected as input to all neurons of the next layer once it is multiplied by specific weights. Each neuron is activated by a function f (activation function), which reflects the possible infinite range of values of the neuron at a predefined interval, usually in $[-1,1]$ or in $[0,1]$. A signal fed to the input layer of the ANN is transmitted through the hidden layer to the output layer, where the output signal of the ANN is generated.

The typical operation of an ANN is divided into two stages:

- the **training** stage
- the **recall** stage.

During the training stage, a sequence of inputs and desired outputs known as training patterns are given to the ANN. At this stage, the weighting factors of the ANN, which are initially given small random numbers, are appropriately adjusted so as to minimize the error of the output of the ANN with respect to the desired output. The training of the ANN is a time-consuming iterative process – especially when a large number of input–output patterns is used – and usually takes place in advance (off-line).

Once the training stage is completed, the recall stage begins. At this stage, only the inputs are given to the ANN and the latter calculates the output according to its training. Computationally, the recall stage requires the transmission of the input vector through the ANN and the generation of the output vector and is extremely fast.

Relevant bibliography dealing with the design and use of ANNs for PV and wind generation forecasting can be found in [4,5].

For the purposes of this project, a suitable ANN has been developed and trained for the forecasting of both the PV and wind power generation one hour ahead. In order to predict the value of the PV/wind power generation two hours ahead, the predicted value of the next hour is used as input for the prediction of the PV/wind generation for the second hour ahead. Following the same logic iteratively, in order to predict the PV/wind production t hours ahead, the predicted value of hour t-1 must be used as input for the prediction of the PV/wind generation during hour t. Thus, this continuous rolling update of the inputs of the ANN allows for the forecasting to be extended up to the desired forecast horizon. In Table 1 the inputs and the output of the ANN models for the PV and wind power generation forecast are presented.

Once the training of the ANN is completed, the time series of the residuals of the training is calculated as the difference between the forecasted values (using the trained ANN) and the historical values (real measurements).

2.1.3. Scenario generation algorithm

Once the appropriate model for the PV or wind generation forecasting is determined, a technique for the generation of the initial set of scenarios is implemented on the basis of a sampling approach [6].

In any of the above forecasting models (ARIMA or ANN model), the time series of the residuals (white noise) follows a normal distribution with zero mean and standard deviation σ, i.e. $\varepsilon_t \sim N(0,\sigma)$. In this context, the procedure to generate a set of scenarios for a stochastic process $\boldsymbol{Y}$ (e.g. PV or wind power production) comprises an iterative process based on the random generation of white noises in order to develop a discrete approach of the stochastic process represented by a set of scenarios. Based on this logic, an appropriate algorithm has been developed to generate a set of scenarios for the day-ahead PV and wind power generation [6]. In this algorithm N_T denotes the desired number of periods, while N_Ω denotes the desired number of scenarios. The above scenario generation algorithm is illustrated in the block diagram of Fig. 2. An illustrative example of the above algorithm with the use of a typical forecasting model AR(3) is given in Fig. 3.

Many stochastic processes associated with the management of the power systems and the operation of the electricity markets (where applicable) are statistically dependent. For instance, the energy injection from spatially close wind farms or PV stations frequently follows similar patterns. Modeling this statistical correlation is of the utmost importance for the System Operator, who is responsible for the management and the operation of the power system, as well as for producers owning RES plants at adjacent geographical sites, who wish to schedule optimally their electricity production.

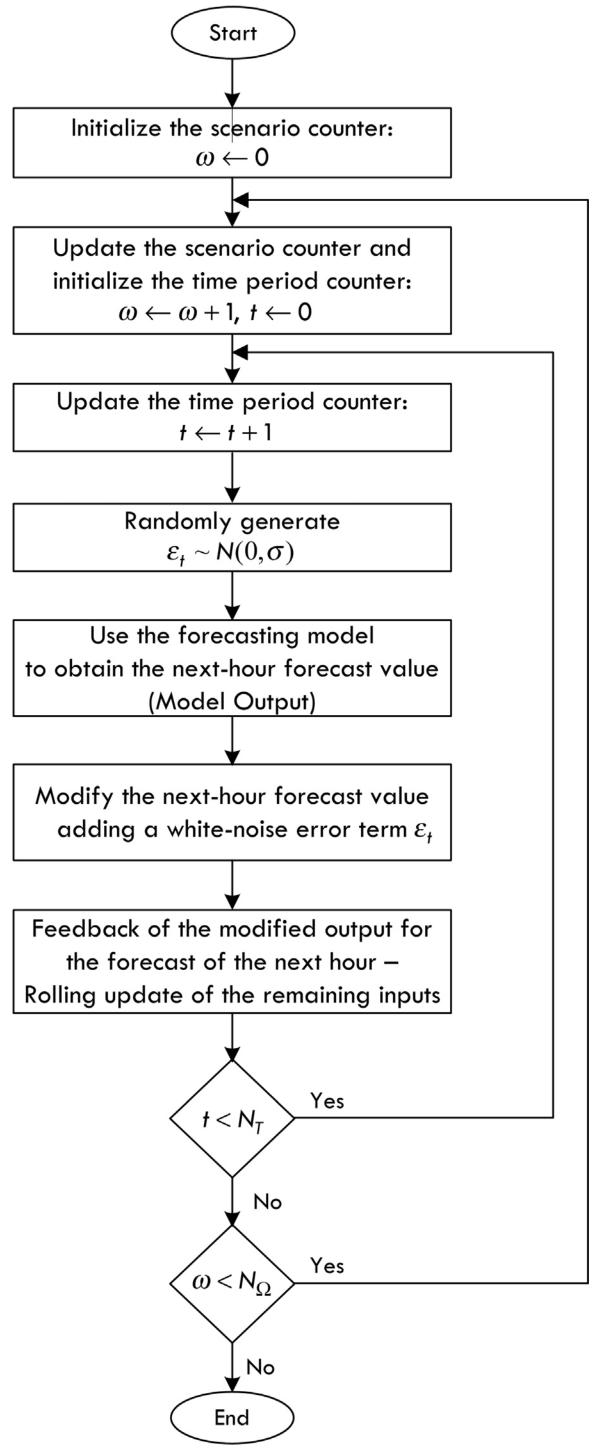

Fig. 2. Scenario generation algorithm.

Relevant works on the concept of cross-correlation of electricity production from RES plants as well as reported techniques for the efficient generation of statistically dependent (cross-correlated) scenarios have been located in the literature [7–13].

In order to account for the statistical correlation of the power output from neighboring RES plants, in the framework of this project an appropriate algorithm already described in [6]

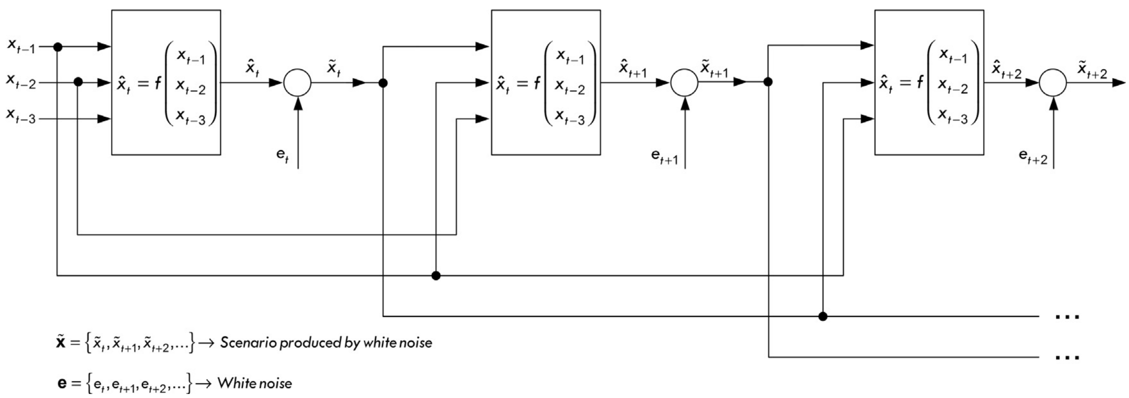

Fig. 3. Scenario generation algorithm using forecasting model AR (3).

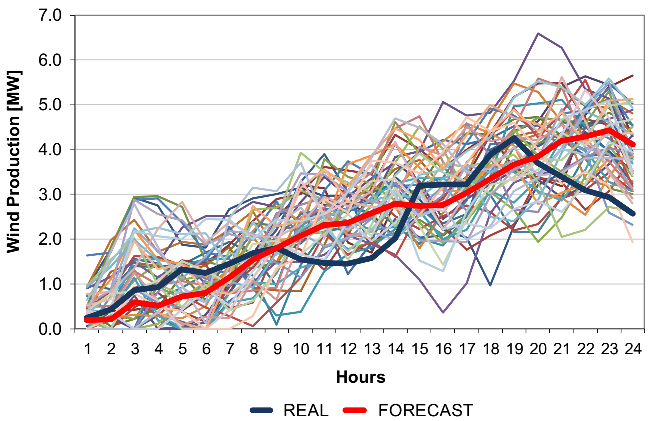

Fig. 4. Extended set of scenarios for wind park "Anemos Aiolikis".

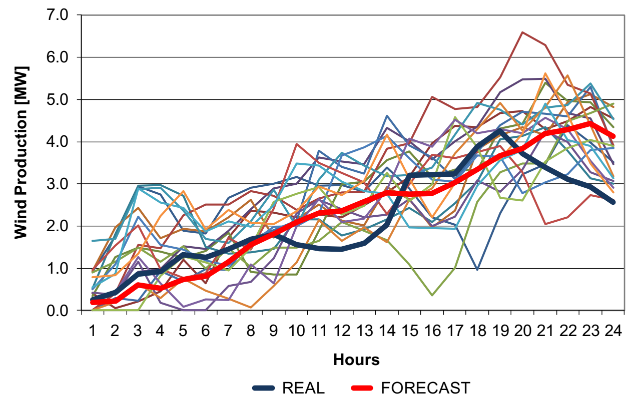

Fig. 5. Reduced set of scenarios for wind park "Anemos Aiolikis".

was implemented for the generation of spatial and temporal cross-correlated scenarios regarding the RES electricity injection.

2.1.4. *Scenario reduction techniques*

Usually, a large set of scenarios is required to ensure that the sampling approach described in the previous section represents the stochastic process accurately. However, since the computational performance of the stochastic programming models is highly dependent on the size of the scenario set, a compromise between the necessary number of scenarios and the computational burden of the associated stochastic programming model needs to be made, so that the problem can be solved using acceptable computational resources. For this purpose, appropriate scenario reduction techniques are usually applied.

A scenario reduction technique aims at reducing the size of the set of scenarios as much as possible, while at the same time the stochastic information enclosed in the original set is affected as less as possible. In other words, the optimal solution of the stochastic optimization problem using the reduced set of scenarios should remain close to the optimal solution obtained using the extended (original) set of scenarios. Various scenario reduction techniques have been reported in the literature so far [14–20].

The scenario reduction methodology implemented is based on the concept of the probability distance [5]. In general, the probability distance allows for quantifying how "close" two different sets of scenarios representing the same stochastic process are. In this context, if a large scenario set is close enough to a reduced one in terms of the probability distance, the optimal solution of the simpler problem (which is formulated and solved using the reduced set of scenarios) is expected to be close to the optimal value of the original problem (which is formulated and solved with the extended set of scenarios). The most common probability distance used in stochastic programming is the *Kantorovich distance* [7], also adopted here. A comprehensive overview of the theoretical background underlying the concept of probability distance is thoroughly presented in [7], while its application to scenario reduction is discussed in detail in [14].

2.1.5. *Indicative results*

Indicative results from the process of creating cross-correlated scenarios for the electricity production of two adjacent wind farms, namely "Anemos Aiolikis" and "Ydroaioliki", located in the prefecture of Chania, Crete, are presented next. Their installed capacity is 6.3 MW and 9.35 MW, respectively. Figs. 4 and 5 illustrate the extended (50 scenarios) and reduced (20 scenarios) set of scenarios for the wind generation of the wind park "Anemos Aiolikis", while Figs. 6 and 7 illustrate the respective extended and reduced set of scenarios for the wind generation of the wind park "Ydroaioliki".

2.2. *Scenario generation for system load*

The scenario generation procedure regarding the electrical load is based, in general, on the same iterative process of random generation of white noises already discussed in Section 2.1 and illustrated in Fig. 2. In the case of the system load, a well-trained ANN model was used as forecasting model.

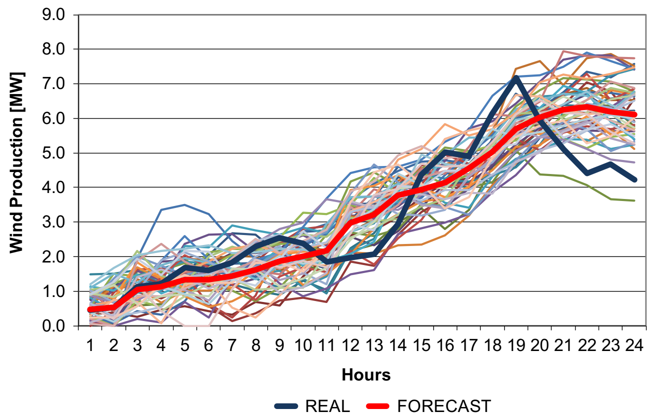

Fig. 6. Extended set of scenarios for wind park "Ydroaioliki".

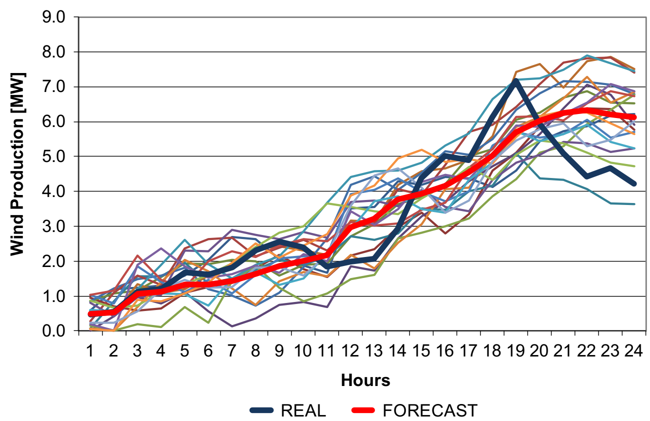

Fig. 7. Reduced set of scenarios for wind park "Ydroaioliki".

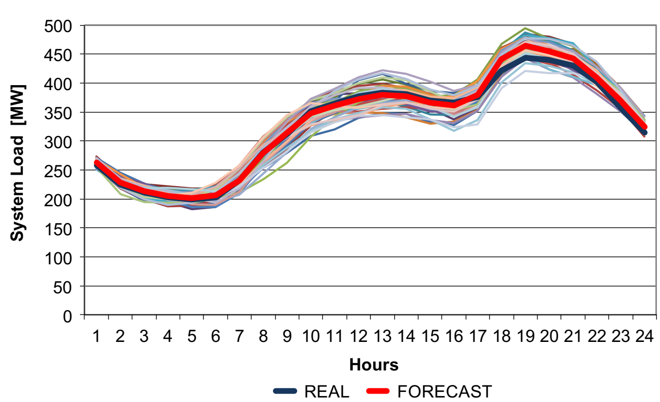

Fig. 8. Extended set of system load scenarios for the power system of Crete.

The ANN used for the system load forecasting is trained taking into account:

- the real values of the electrical load during past hours and days,
- the hour of the day, the day of the week, and the day of the year during which the real values of the load were recorded,
- the maximum and the minimum daily temperature.

Relevant bibliography discussing the design of ANNs for the electrical load forecasting can be found in [21,22].

The application of the relevant scenario generation and reduction algorithms is shown in Figs. 8 and 9, where 50 scenarios for the electrical load of the insular power system of Crete, Greece, with a 24-h forecast horizon were initially created (see Fig. 8) and subsequently transformed to a reduced set of 20 scenarios (see Fig. 9).

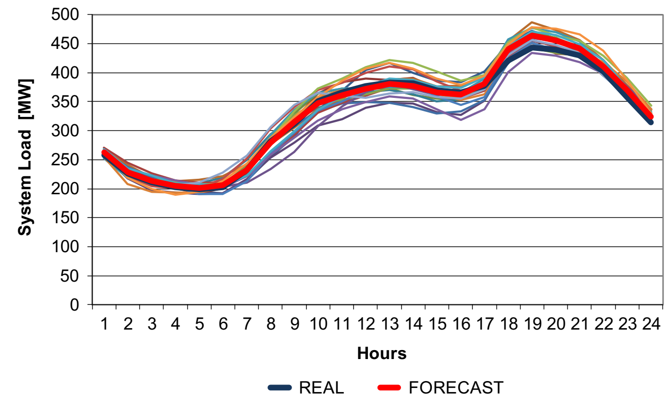

Fig. 9. Reduced set of system load scenarios for the power system of Crete.

2.3. *Scenario generation for unit availability*

One of the main sources of uncertainty to be taken into account for the modeling of the short-term operation of the power system is the generating units' availability i.e. the ability of the unit to produce at its nominal capacity or its inability to fully or partially produce electricity due to a forced outage.

In order to model the availability or unavailability of generating units, availability scenarios are usually created. In this project, the generation of unit availability scenarios is based on a widely used technique, which involves creating "availability" and "non-availability" states using a two-state Markov model.

The availability history of a generating unit is usually represented by a two-state time series, where *Up* = "available" and *Down* = "unavailable", as shown in Fig. 10. This dynamic sequence of states is constructed using a two-state Markov model, as illustrated in Fig. 11.

According to Fig. 11, each generating unit is characterized by a failure rate λ (times per year) and a repair rate μ (times per year) or, equivalently, by the unit mean time to failure $t_{mean}^{Up} = 8760/\lambda$ (in h) and the unit mean time to repair $t_{mean}^{Down} = 8760/\mu$ (in h).

The time t^{Up} for which the unit remains available until the next failure and the time t^{Down} for which the unit is off-line until it becomes available again, can be considered as random variables following exponential distribution, with time constants t_{mean}^{Up} and t_{mean}^{Down}, respectively, as follows:

$$F(t^{Up}) = 1 - e^{\lambda t^{Up}/8760} \tag{2}$$

$$F(t^{Down}) = 1 - e^{\mu t^{Down}/8760} \tag{3}$$

Using the inverse transform method [23], the random time to the next failure (status "*Up*") and the random time to the next repair (status "*Down*") are given, respectively, by the following expressions:

$$t^{Up} = F^{-1}(y) = -\frac{8760}{\lambda}\ln(1-y) = -t_{mean}^{Up}\ln(1-y) \tag{4}$$

$$t^{Down} = F^{-1}(y) = -\frac{8760}{\mu}\ln(1-y) = -t_{mean}^{Down}\ln(1-y) \tag{5}$$

where y is a random variable uniformly distributed in [0,1].

Therefore, expressions (4)–(5) allow for the generation of k random samples t_k^{Up}, t_k^{Down} through the generation of random samples y_k from the uniform distribution in [0,1].

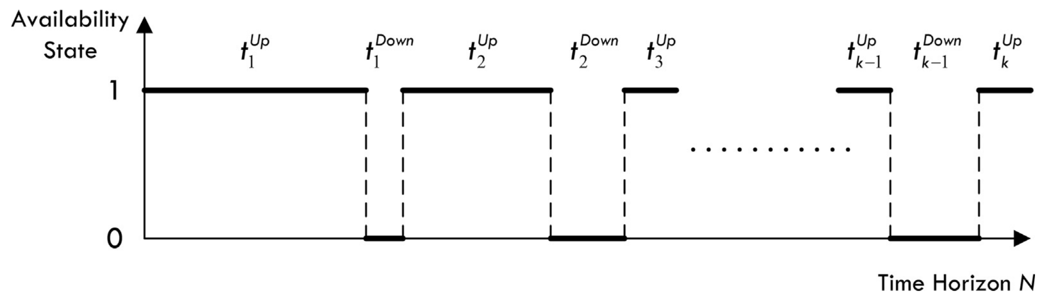

Fig. 10. Unit availability state sequence.

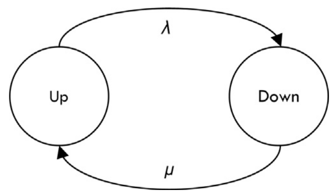

Fig. 11. A two-state Markov model.

For short-term operation (e.g. 24-h time horizon), the time to next repair t_k^{Down} can be neglected, given that when the unit becomes unavailable during a single hour of the 24-h horizon it is considered to remain unavailable up to the end of the 24-h period. For longer time horizons, the generation of k random samples shall be repeated until the time series of the successively produced t_k^{Up}, t_k^{Down} covers the respective time period.

Finally, the availability state $av_{i,t,\omega}$ of unit i for hour t and scenario ω is defined as follows:

$$av_{i,t,\omega} = 1 \quad \forall i,\ t_{k-1}^{Down} < t < t_k^{Up},\ \omega$$

$$av_{i,t,\omega} = 0 \quad \forall i,\ t_k^{Up} < t < t_k^{Down},\ \omega$$

3. Scheduling models for the short-term operation of insular power systems

3.1. Problem description

Owing to their small-size and autonomous nature, insular power systems are simpler to monitor and control than large, multi-area interconnected power systems. There are no seams issues and no low frequency inter-area oscillations threaten the integrity of insular power systems. However, owing to the same reasons, insular power systems are more vulnerable to high RES penetration: they cannot import flexible generation from neighboring power systems when wind is not blowing and sun is not shining and cannot export the excess renewable generation of windy and sunny days to their neighbors through the interconnections. In addition, they cannot take advantage of the renewable generation "portfolio effect", i.e. the fact that renewable generation becomes more predictable and less variable when aggregated over a wide geographic area. Finally, the effects of increased renewable penetration on the system inertia and the system primary frequency response characteristic are harder to manage in the absence of the help from neighboring systems.

Whichever the nature of the power system is (i.e. insular or interconnected), an important criterion for the optimal short-term operation of a power system is to meet the variable load demand with minimum operating cost using an optimal mix of the available generating units, according to their operating characteristics. System Operators regularly use short-term scheduling models in order to fulfill this objective, among which Unit Commitment is considered to be one of the best available options for longer time horizons (e.g. one day or several hours ahead). For near to real-time horizons (e.g. 5 min or 15 min ahead), Economic Dispatch is usually used. In this case, the commitment status of the conventional generating units for each dispatch interval has already been determined by the most recent unit commitment solution and economic dispatch aims only at dispatching the on-line units solely respecting their ramp rates and technical limits to meet the system load at least cost.

In general, Unit Commitment (UC) is a complex optimization problem, where the System Operator (SO) aims at minimizing the total production cost over the scheduling horizon. The total production cost comprises the fuel costs, which are primarily associated with the operating status and the production level of the generating units, the start-up costs and the shut-down costs. As a result, the UC problem has been traditionally solved in centralized power systems to determine the best possible commitment status, the start-up/shut-down sequences and the respective power outputs for all available generating units in order to satisfy the forecasted demand and the system-wide reserve requirements in all time intervals of the scheduling horizon. Moreover, the SO has to respect various generating unit constraints (such as the minimum up/down times, the start-up/shut/down trajectories, etc.), which further reduce his flexibility to select which generating units to start-up and/or shut-down.

In this sense, the UC optimization problem has the following form:

Minimize [Total Production Costs] = [Fuel Costs + Start-Up Costs + Shut-Down Costs]

Subject to:

a) Unit capacity limits.
b) Unit minimum up/down times.
c) Unit ramp rate limits.
d) Unit initial conditions and status restrictions (must-run, fixed-MW, unit availability).
e) System power balance.
f) System reserve requirements.
g) Network constraints.

Constraints (a)-(d) are the local unit-wise constraints, while constraints (e)–(g) are the system-wide coupling constraints. The specific nature of the UC problem has been exploited by SOs through various solution algorithms, in order to achieve a feasible and as close to optimal solution as possible. It should be noted that for interconnected power systems the UC system constraints must be accordingly modified to take into account the interchange schedules and the tie-line constraints.

The Economic Dispatch (ED) problem formulation is simpler than the UC formulation, since the objective function comprises only the

fuel costs and the problem is subject only to the unit-wise constraints (a), (c) and the system-wide coupling constraints (e)–(g).

The critical problem of Unit Commitment (UC) in a power system has been addressed by many different novel approaches and algorithms so far. These approaches range from simple exhaustive enumeration below [24,25] and priority listing methodologies [26–28] to dynamic programming [29–35], artificial intelligence [36–42] and Lagrangian Relaxation techniques [43–48]. Lately, more advanced mixed-integer linear programming (MILP) models have been adopted [49–56], following the rapid growth of state-of-the-art hardware and software systems. Finally, stochastic optimization [57–61] and robust optimization techniques [62–68] are among the most popular emerging trends to deal with related optimization problems under uncertainty.

3.2. Description of the proposed optimization models

The MILP approach has been proposed in the last decade as a viable and efficient alternative methodology for solving various optimization problems associated with the short-term operation of power systems, such as the UC problem. MILP models have been widely applied, since most SOs along with the research community recognized that critical decisions associated with the operation of the power system can be effectively represented by integer (more specifically binary) variables and, therefore, classical linear programming approaches could not be used to explicitly model and solve such complex problems. In MILP formulations, the commitment decisions denoting practically the on/off status of the generating units in various operating phases (e.g. off-line, start-up, dispatchable, shut-down, etc.) are modeled using binary variables, while the power output, reserve contribution and power flow decisions are modeled using continuous variables.

In this project, the short-term operation of the insular power system is modeled using three distinct MILP-based optimization models, namely as follows:

- A Rolling Day-Ahead Scheduling (RDAS) model,
- An Intra-day Dispatch Scheduling (IDS) model, and
- A Real-time Economic Dispatch (RTED) model.

Fig. 12 illustrates the general input-output data structure of the aforementioned MILP models. It is mentioned that the RDAS and IDS models have been developed either in a deterministic framework (considering all unit and system parameters deterministically known for the respective scheduling period) or in a scenario-based stochastic programming framework to account for uncertainties associated with the random unit and system parameters (e.g. system load, RES production, unit availabilities, etc.), as already discussed in Section 2.

The solutions of all above models are coordinated aiming at the maximization of the zero variable cost RES injection simultaneously minimizing the total operating cost of the conventional (thermal) generating units in the insular power system.

Specifically, the RDAS model solves the short-term UC problem with an hourly time resolution, where a simultaneous multiple-hour co-optimization of energy and reserve resources is performed under a large set of unit and system constraints (e.g., unit start-up and shut-down procedures, minimum-up/down time constraints, min/max power output restrictions, ramp-rate limits, system reserve requirements, transmission limits, etc.). The RDAS model is typically solved twice for each dispatch day (day D): once prior to the beginning of the dispatch day (e.g. at 21:00 of day D-1), covering the entire day-ahead scheduling period (24 h of day D), and once few hours prior to noon of day D (e.g. at 10:00 a.m.) covering the second half of day D (i.e. hours 13–24), as updated forecasts regarding the system and unit parameters (e.g. system load, unit availabilities, RES injection) are made available during the progress of day D.

The solution of the RDAS model provides the commitment status and dispatch scheduling for all generating units (conventional and RES) during the respective scheduling period (24 h or 12 h) under study. In this context, the optimal commitment status of slow base-load units is considered as binding (fixed decisions) for the formulation and solution of the intermediate IDS models that follow, while the optimal commitment status and dispatch scheduling for all other units (fast units and RES plants) provided by RDAS are indicative.

The IDS model follows in general the formulation of the RDAS model. The main difference lies in that the UC problem is now solved every twenty (20) min on a multiple-hour basis (typically four (4)h) with a 20 min time resolution. Since the solution of the RDAS models provides the commitment of the slow units for day D (binding start-up and/or shut-down decisions), which is considered to remain unchanged unless a unit forced outage takes place,

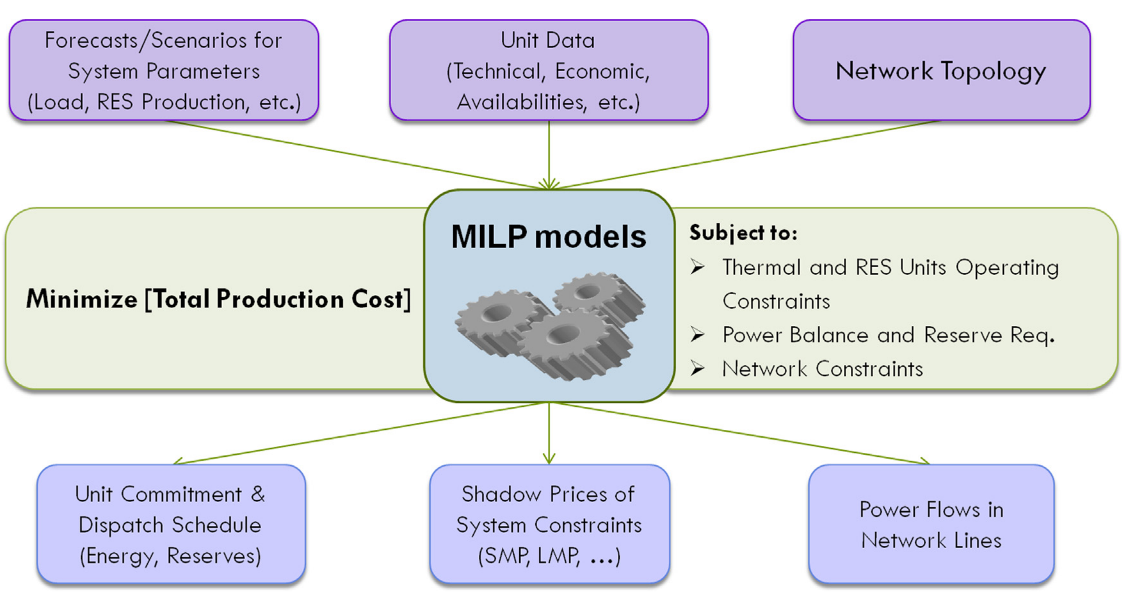

Fig. 12. General structure of MILP models.

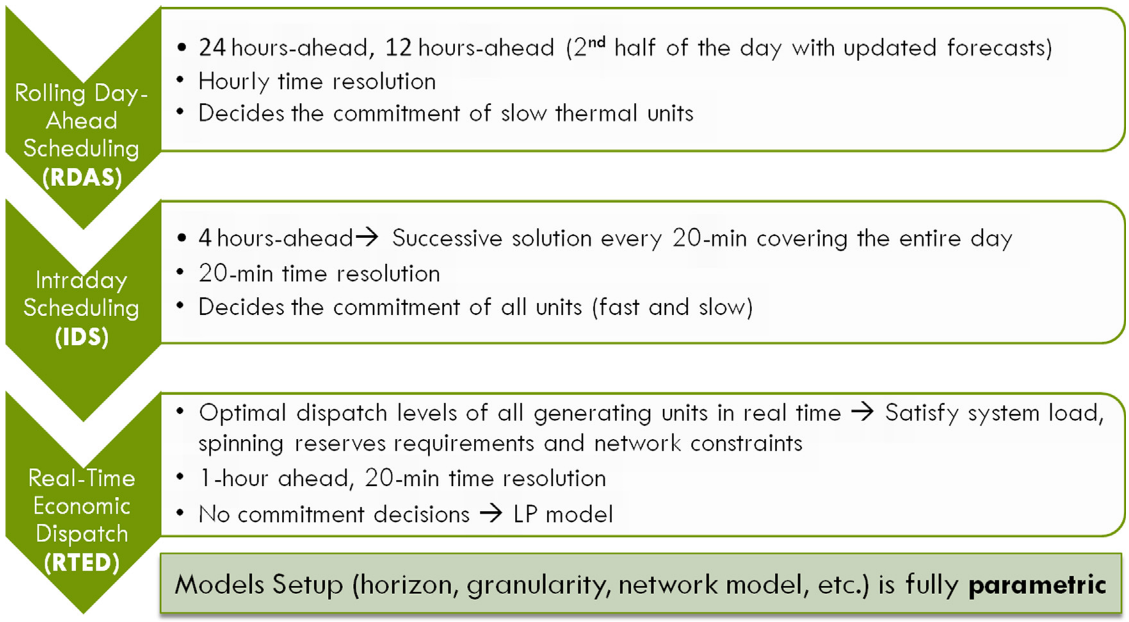

Fig. 13. Scheduling models characteristics.

the committed slow units are modeled as must-run units in the IDS runs during day D. In this sense, the IDS model is solved successively during day D deciding only on the commitment status of the fast thermal units and RES plants (if applicable) as well as the dispatch scheduling of all (slow and fast) units.

Finally, the RTED model is implemented for the determination of the optimal generation dispatch levels of all generating units in real time (e.g. every 20 min) to satisfy the system load demand and the spinning reserves requirements. The main feature of RTED model is that no commitment decisions are taken, since the commitment status of all generating units for each dispatch interval has already been determined by the most recent RDAS and IDS models solutions. Therefore, RTED can be considered as a special case of the aforementioned MILP unit commitment problem, since it is, in fact, a Linear Programming (LP) problem (no binary decision variables are used) and aims at dispatching the online units respecting only their ramp rates and technical limits to meet the system load at least cost. Following the current trend of advanced electricity markets [69–71] that recently adopted RTED models with a look-ahead horizon in order to deal more efficiently with the unpredictability and variability of RES, the proposed RTED model has been formulated for a 20 min dispatch period in conjunction with a look-ahead horizon of one hour.

Finally, it is noted that both the time horizon and time resolution of all three scheduling models have been chosen according to the provisions of the Greek Grid Code for non-interconnected islands, which is currently under public consultation. However, they are all parametric and can be easily adapted to the needs of every single insular power system.

Fig. 13 illustrates the main characteristics of the three distinct scheduling models, while the coordination sequence of the three scheduling models along with an indicative scheduling timeline is illustrated in Fig. 14.

3.3. Test results

The developed MILP models have already been tested on the power system of Crete, Greece, which is a large insular system currently comprising 25 conventional thermal units of different technologies, with a total installed thermal capacity of 799 MW. In addition, there are 29 wind parks and around 2800 PV installations (990 ground-mounted and 1806 rooftop systems) with a total installed capacity of 184 MW and 94 MW, respectively. Table 2 presents an overview of the generation mix of the insular power system of Crete at the end of 2013.

Figs. 15–20 illustrate indicative results from the application of the scheduling models in the power system of Crete. Two different cases have been examined, which are differentiated only in terms of the wind energy production distribution during the day. It is noted that the total available wind generation (in MWh) is identical in both cases. In this sense, the effect that the wind energy generation profiles may have on the short-term scheduling of the entire generation mix is analyzed. Specifically, in Case 1 (Morning wind) wind blows strongly during the first hours of the day and gradually decreases during the evening and night hours. On the contrary, in Case 2 (Afternoon wind) wind generation is weak during the early morning hours and gradually increases and reaches its peak during the last hours of the 24 h scheduling horizon.

Figs. 15 and 16 illustrate the day-ahead scheduling per unit type for both cases. In both cases, Combined Cycle Gas Turbine (CCGT) is considered a must-run unit, since its continuous operation is strictly required by the SO in order not only to alleviate voltage stability issues in the west side of the island where the CCGT unit is located, but also to contribute significantly to different types of spinning reserves (i.e. primary, secondary, tertiary). In the case of high morning wind (Case 1), the low system load during the early morning hours in conjunction with the fact that base-load thermal units cannot operate below their minimum power output as well as they cannot be shut-down and subsequently start-up immediately due to critical technical and economic constraints (e.g., long minimum up/down times, high start-up costs, provision of reserves, etc.) lead to a notable wind curtailment of 76.3 MWh/day, which correspond to 3.3% of the total daily available wind production for this case (see Fig. 15).

On the contrary, in the case of high afternoon wind (Case 2) these issues are eliminated (wind curtailment falls to 4.3 MWh/day or 0.002%), since the wind generation contributes mainly to

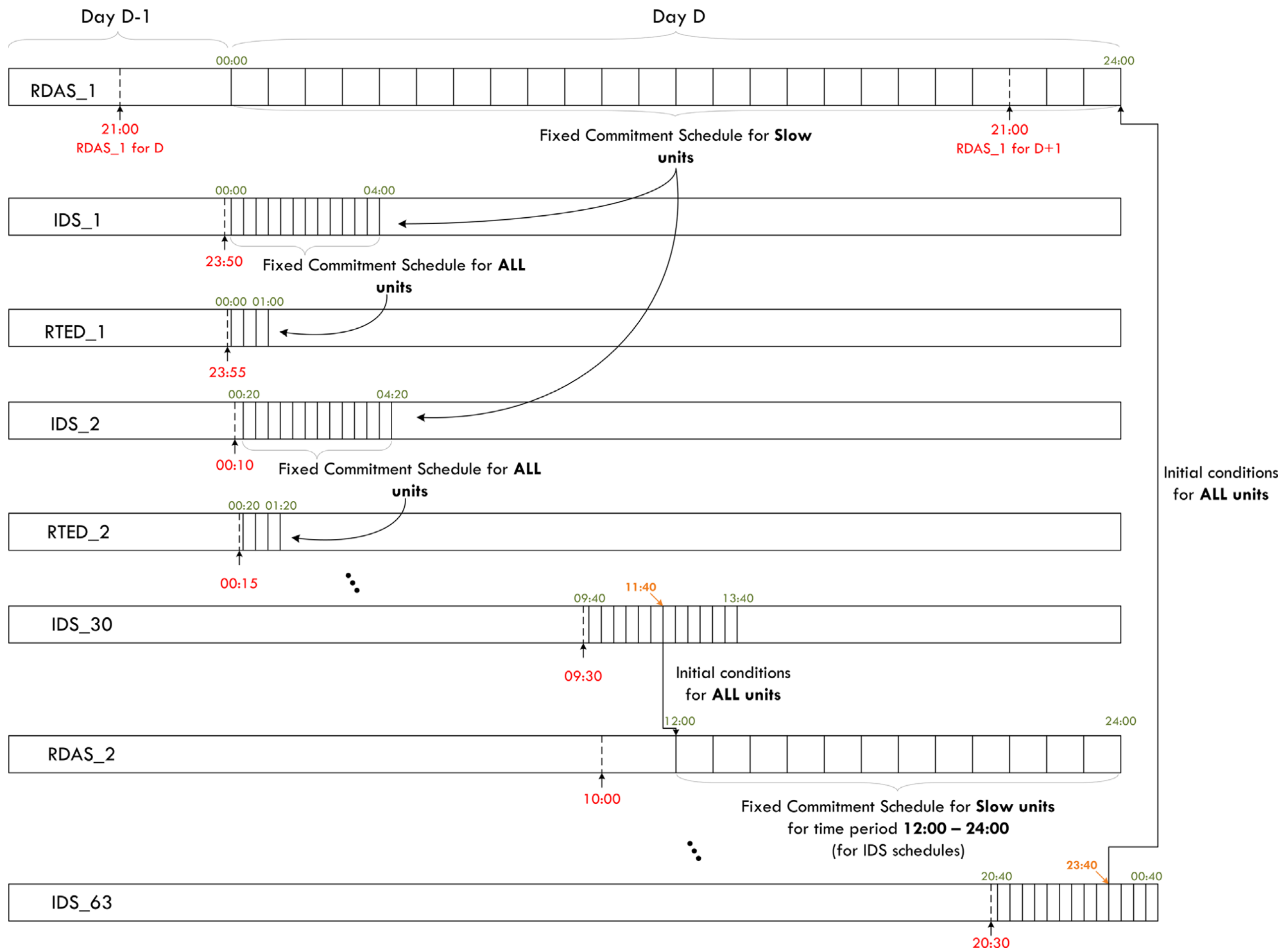

Fig. 14. Coordination sequence of scheduling processes.

Table 2
Crete power system overview (December 2013).

Unit Technology	Unit Fuel	Number of Units	Installed Capacity [MW]
Steam	Fuel oil	7	198
Combined-cycle gas turbine (CCGT)	Diesel	1	132
Open-cycle gas turbine (CCGT)	Diesel	11	324
Internal combustion engine (ICE)	Fuel oil	6	145
Wind	–	29	184
PV	–	2800	94
Total	**–**		**1077**

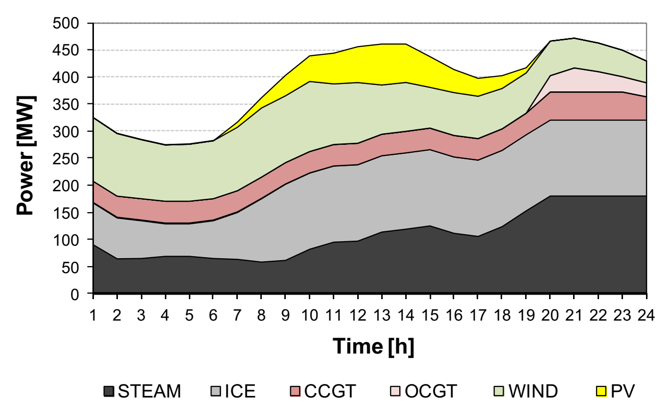

Fig. 15. Day-ahead scheduling – Morning wind (Case 1).

the shaving of the noon and the evening peak load, also restricting significantly the operation of high-cost thermal units, such as the Open Cycle Gas Turbine (OCGT) units (Fig. 16), which in Case 1 are deemed necessary to serve the evening peak-load (see Fig. 15).

Figs. 17 and 18 illustrate the total energy and reserves contribution provided by all conventional thermal units for the two cases examined. The system reserve requirements are determined on a regular basis by the SO according to the specific needs of the power system taking also into account the RES share. The dashed and dotted red lines denote the total maximum and minimum power output of all conventional units that are on-line in each hour of the scheduling period, respectively. It is clear that the power output of all thermal units plus/minus the corresponding total contribution in spinning reserves (i.e. R1up: primary-up, R1dn: primary-down, R2up: secondary-up, R2dn: secondary-down, R3S: tertiary spinning) do not exceed the corresponding technical limits (i.e. maximum/minimum power output) of the thermal generation system.

Figs. 19 and 20 illustrate the distribution of the total daily production cost in the different conventional thermal unit types for the two cases studied. As expected, in Case 1 where wind generation substitutes mainly low-cost thermal units (i.e. steam and Internal Combustion Engine (ICE) units) during the early morning hours (see Fig. 15), the total system production cost is

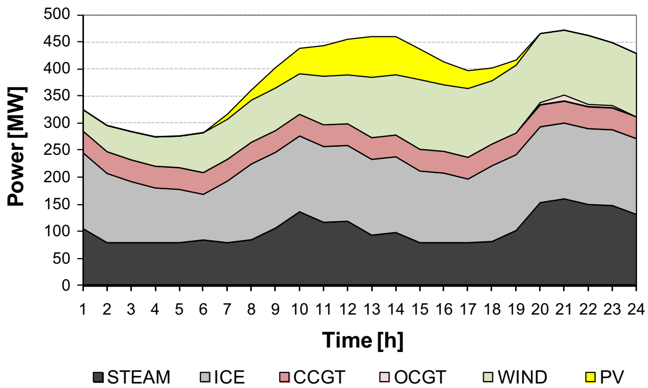

Fig. 16. Day-ahead scheduling – Afternoon wind (Case 2).

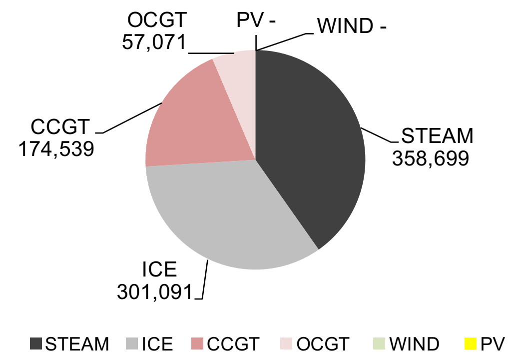

Fig. 19. Total daily production cost – Morning wind (Case 1).

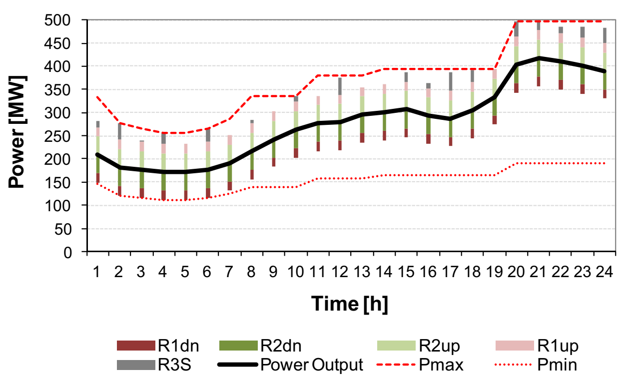

Fig. 17. Energy and reserves contribution from conventional units – Morning wind (Case 1). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

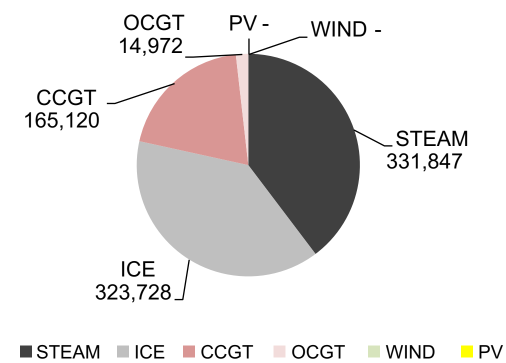

Fig. 20. Total daily production cost – Afternoon wind (Case 2).

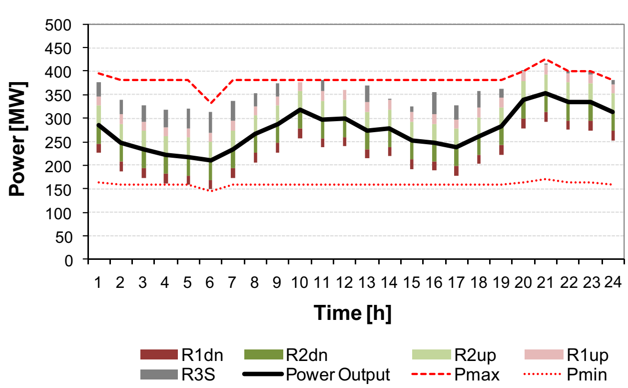

Fig. 18. Energy and reserves contribution from conventional units – Afternoon wind (Case 2). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

equal to €907,838 with the share of OCGT units' production cost being equal to 6.3% (=€57,031/€907,838). On the contrary, in Case 2 where wind generation substitutes mainly the energy production of medium-/high-cost thermal units (i.e. CCGT and OCGT units) during the evening hours (see Fig. 16), the total system production cost falls to €835,668 (−7.95% as compared to Case 1) and the share of OCGT units' production cost falls to 1.8% (= €14,972 / €835,668).

4. Conclusion

In this paper an overview of various methodologies and mathematical optimization models developed in the context of the EU-funded project SiNGULAR towards the optimal short-term scheduling of electricity generation in insular electricity networks was presented. Methodologies that combine a scenario generation technique of an original extended set of scenarios with a technique to reduce the number of scenarios while capturing the spatial and temporal correlations of the corresponding variables have been discussed. Indicative results from their application in the pilot system of the island of Crete, Greece, prove the efficiency of the applied procedures.

Additionally, the main features of three MILP-based optimization models developed for the short-term scheduling of insular power systems along with an indicative coordination plan and proposed timeline were analyzed in detail. Simulation results showed that, in power systems with high share of renewable energy, the daily wind energy generation profiles may have a vital impact on the short-term scheduling of the entire insular generation mix in terms of wind energy curtailment, short-term operation of conventional thermal units and total system production cost. In this sense, new challenges arise regarding the efficient and reliable short-term operation of insular electricity networks with high RES penetration. These challenges call for the design and implementation of new emerging methods and tools, such as the demand side management, the electrical energy storage, the concept of virtual power plants, etc, in the following years.

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